Applied Energy 92 (2012) 26–37

Contents lists available at SciVerse ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Forecasting natural gas consumption

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ARTICLE INFO

Article history:
Received 28 June 2011
Received in revised form 18 October 2011
Accepted 1 November 2011
Available online 27 November 2011

Keywords:
Forecasting natural gas consumption
Predicting natural gas demand
Natural gas forecasting models

ABSTRACT

Publishing papers in the area of forecasting natural gas consumption has begun in the middle of last century and led to a tremendous surge in research activities in the past decade. This paper presents a state-of-the-art survey of forecasting natural gas consumption. Purpose of this paper is to provide analysis and synthesis of published research in this area from beginning to the end of 2010, insights on applied area, used data, models and tools to achieve usable results, in order to be helpful base for future researchers.

Contents

1. Introduction

Forecasting natural gas consumption was investigated in several different areas, on world level, national level, on gas distribution system level, on commercial and residential sectors, and finally, on individual customer level, using various data in building forecasting models such as economic parameters, weather data, past natural gas consumption data, past energy consumption data, mathematical and engineering calculations, software simulation data, survey data of households and other various parameters, such as days of the week. Forecasting horizon varies from a few hours ahead to a few decades ahead. This paper is organized as follows: Section 2 is historical overview of natural gas forecasting, Section 3 gives an overview of applied area, Section 4 gives an overview of forecasting horizons, Section 5 gives an overview of used data, Section 6 gives an overview of used forecasting tools and Section 7 is the conclusion of the paper.

2. Historical overview

When natural gas was first commercially used in Britain around 1785, it was produced from coal [1], whereas soon after, to nowadays it has been produced by drilling the Earth core. With the development of gas distribution systems and increasing consumption, over time some question were raised: How much gas will we consume? How long will we have natural gas form the Earth core? How big a pipeline do we need? In every decision making process

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0306-2619/$ - see front matter © 2011 Elsevier Ltd. All rights reserved.
doi:10.1016/j.apenergy.2011.11.003

forecasting is one of the main tools. So it began in the gas market. In the middle of the 20th century, Verhulst [2] investigated the demand for manufactured gas in French gas industry, with available data related to a sample of 46 firms divided into three groups, building a model defined by demand equation, equation of production and the equilibrium equation with respect to price and income. Almost at the same time, Hubbert investigated the life circle of fossil fuel fields in his papers and he described their characteristic life circle [3,4]. In his works, he established Hubbert curve model from mathematical relations involved in the complete cycle of production of any exhaustible resource, in production rate dQ/dt over time diagram, which was later used in many papers as a forecasting tool for fossil fuel production and consumption. Hubbert's works have been often used as base or as reference since publishing them till nowadays, although some of researchers approved his work [5–7] whereas some did not [8]. In 1966 Balestra and Nerlove [9] used econometrics parameters in residential and commercial sectors, using an ordinary least square model to forecast demand for natural gas. In 1973 forecasting natural gas demand was used by Tinic et al. [10] as a tool for economic evaluation of rural gasification plan. Using Balestra and Nerlove generalized model, Berndt and Watkins [11] in 1977 attempted to estimate an econometrics model for natural gas demand in residential and commercial market sectors in British Columbia and Ontario. In 1981 Beierlein et al. [76] estimated demand for electricity and natural gas in northeastern United States. In 1983 a few days ahead forecast was performed by Piggott [12]. In 1987 regression analysis was used for evaluation of aggregate monthly industrial demand for natural gas in the USA by Herbert et al. [13]. In the same year, Herbert [14] analyzed monthly sales of natural gas to residential customers in the United States using regression relationship to estimate monthly and annual natural gas deliveries. In 1988 Werbos [15] discussed application of back-propagation to recurrent gas market. Three years later Liu and Lin [16] studied the consumption of natural gas in Taiwan within residential sector using monthly and quarterly data employing price and temperature variables. Using microeconomic consumption data, in 1994, Lee and Singh [17] investigated patterns in residential gas and electricity consumption. In the same year, Brown et al. [18] developed models based on feed-forward artificial neural network to predict gas consumption on a daily basis. Two years later, in 1996, Nagy [19] used econometric models to estimate the demand for natural gas in Kuwait, Brown and Iftekhar [20] used feed-forward artificial neural network models to predict daily gas consumption in two regions in Wisconsin served by Wisconsin Gas Company, Smith et al. [21] used expert systems based forecasting tool in predicting gas demands by regional gas company and compared its results with the result obtained from traditional techniques, Suykens et al. [22] proposed accurate neural network model for the gas consumption in Belgium, while in Australia Bartels et al. [23] used statistical method of conditional demand analysis (CDA) to estimate the end-use consumption of natural gas. The following year, Sailor and Munoz [24] developed a methodology for assessing the sensitivity of electrical and natural gas consumption to climate on regional scales, Al-Jarri and Startzman [5] took a risky task of predicting the world's future supply and demand for petroleum liquids (crude oil and natural gas liquids) to the year 2050. In 1999 Khotanzad and Elragal [25] used a combination of artificial neural networks composed of two stage systems. The following year Khotanzad et al. [26] expanded work on combination of artificial neural network forecasters for predicting of natural gas consumption and Durmayaz et al. [74] used degree-hour method to estimate residential heating energy requirement and fuel consumption in Istanbul. Also, at the same time, Al-Fattah and Startzman [27] forecasted the world natural gas supply fifty years ahead using the 'multicyclic Hubbert' approach. In 2001 Gumrah et al. [28] used degree-day concept (DD) for modeling gas demand in the case study of Ankara. In 2002 Tahat et al. [29] used thermal analysis computer system (TAS) to simulate and predict energy consumption in constructing process of low-energy house in the Mediterranean climate in Jordan, and after having built it, they measured its thermal performance. In 2003 Poland's natural gas consumption was investigated by Siemek et al. [30]. They used an adaptation of Hubbert model to predict natural gas consumption forty years ahead. In the same year, Sarak and Satman [31] used a degree-day method to estimate residential heating natural gas consumption in Turkey, so it could be used for designing distribution grids of natural gas. In 2004 Gorucu et al. [32] used artificial neural networks to evaluate and forecast gas consumption in the city of Ankara, Cho et al. [33] examined the effect of measurement period on accuracy of predicted annual heating energy consumption of building, Gorucu and Gumrah [34] developed statistical multivariable regression analysis to understand the factors affecting gas demand and to forecast gas consumption for the capital city of Ankara using optimistic and pessimistic scenarios, Aras and Aras [35] divided the year into a heating and non-heating season in order to obtain appropriate models for forecasting residential monthly natural gas consumption, Gil and Deferrari [36] presented a model intended to predict mainly the residential and commercial natural gas consumption in urban areas, for short and intermediate ranges of time, daily and one to five years ahead, Imam et al. [37] used Multicyclic Hubbert model, improved original Hubbert model, as usable technique to forecast future production trends, Elragal [38] proposed new technique for improving artificial neural network (ANN) prediction using Fuzzy–Genetic model and Cavallo [8] showed why forecasts of world and regional peak oil and natural gas production by using Hubbert's methodology usually have failed. The following year, Gutierrez et al. [39] examined the possibilities of using a Gompertz-type innovation diffusion process as a stochastic growth model of natural-gas consumption in Spain, Viet and Mandziuk [40] analyzed several approaches to predict natural gas consumption in two different regions in Poland, with neural and fuzzy neural systems, Thaler et al. [41] described empirical model for prediction of energy consumption in a distribution systems, and Pelikan and Simunek [42] discussed a possibility to connect the natural gas consumption prediction module with a risk management module in order to gain the optimal regulation design strategy (minimal loss) or the optimal gas selling strategy design (maximal profit). In 2006 Musilek et al. [43] solved the problem of seasonal dependency with a recurrent neural network used as a gate for a statistical mixture model. In the same year, Gelo [78] analyzed an econometric modeling of average gas consumption in Zagreb, Croatia. The following year, 2007, Vondracek et al. [44] presented a statistical approach to natural gas consumption estimation of individual residential and small commercial customers, Potocnik et al. [45] proposed a strategy to estimate forecasting risk, Huntington [46] developed a statistical model of industrial natural gas consumption based on historical data in United States, Sanchez-Ubeda and Berzosa [47] presented a novel prediction model that provides forecasting in a medium-term horizon (1–3 years) with a very high resolution (days) based on a decomposition approach, Timmer and Lamb, [48] quantified relations between winter (November–February; December–February) temperature and residential gas consumption for the United States east of the Rocky Mountains for 1989–2000, by region and on monthly and seasonal time scales, and Potocnik et al. [49] demonstrated an energy forecasting approach where the energy consumption cycles are analyzed and the information obtained is incorporated into the forecasting model. The following year Brabec et al. [50] predicted the daily natural gas consumption on the level of individual customers, using nonlinear regression model with individual customer-specific parameters, Potocnik et al. [51] discussed practical considerations on building forecasting applications due to economic perspective of forecasting natural gas consumption, with an illustrative example of the Slovenian economic incentive model that motivates natural gas distributors to forecast their future consumption with minimum error, Kizilaslan and Karlik [52] tested several different algorithms in order to find a suitable natural gas energy forecasting model for daily and weekly values of Istanbul by using artificial neural networks (ANN), Aydinalp-Koksal and Ugursal [53] investigated use of conditional demand analysis (CDA) method to model the residential end-use energy consumption on the national level in Canada using survey of household energy use, Aras [54] showed application of genetic algorithms to forecast short-term demand of natural gas in residences, Simunek and Pelikan [55] pre-processed temperature data for the purpose of short-term gas consumption forecasting and Jiang et al. [56] focused their research on three regions: Beijing, Guangdong, and Shanghai in order to identify some of the important factors that might drive natural gas consumption in key demand areas in China. Using the economic optimization model MARKAL, they showed that the level of natural gas consumption is most sensitive to policy scenarios, which strictly limits SO_2 emission from power plants. In 2009 Brabec et al. continued their work on statistical model for construction and application of standardized load profiles [57] and statistical calibration of the natural gas consumption model [58], Kizilaslan and Karlik [59] presented different types of neural networks algorithms based model forecasting gas consumption for residential and commercial consumers in Istanbul, Yoo et al. [60] estimated households' demand function for natural gas by applying a sample selection model using data from a survey of households in Seoul, Ma and Wu [61] used dynamic GM(1, 1) model of Grey theory to forecast the natural gas consumption and production in China from 2008 to 2015, Reynolds and Kolodziej [62] analyzed the US and southern Canadian natural gas supply market using the Hubbert curve model, Tonkovic et al. [63] created prediction model of natural gas consumption on a regional level by using neural networks, Xie and Li [64] introduced Grey modeling method optimized by genetic algorithm for prediction of natural gas consumption, Chen et al. [65] presented the method based on genetic algorithms to determine the weight, which avoids the original limit of the least square method and meets the requirements of model projections through different directions, in order to forecast China's natural gas consumption, and Maggio and Cacciola [6] proposed a model based on a variant of the well known Hubbert curve, to determine the peak and the behavior of the world crude oil and NGL production. In 2010 Azadeh et al. [66] presented an adaptive network-based fuzzy inference system (ANFIS) for estimation of natural gas demand in Iran using daily natural gas consumption, Ma and Li [67] analyzed reserves, distribution, production and utilization of natural gas resources in China, and predicted the future production and consumption of China's natural gas using the Generalized Weng model and the Gray prediction model, Li et al. [68] developed a dynamical system model based on the research accomplishments by the predecessors, in order to keep track of natural gas consumption in the near future and present positive proposals for natural gas policies in China, Xu and Wang [69] used Polynomial Curve and Moving Average Combination Projection (PCMACP) model to estimate the future natural gas consumption in China from 2009 to 2015, Forouzanfar et al. [70] presented a logistic based approach to forecast the natural gas consumption for residential and commercial sectors in Iran, Erdogdu [71] focused on the characteristics of demand and estimated short and long-run price and income elasticities of sectoral natural gas demand in Turkey and forecasted future growth in this demand using an ARIMA modeling, comparing these results with official projections, Toksari [72] presented a heuristic approach to estimate Turkey's natural gas demand based on economic indicators, Dombayci [73] compared hourly heating energy consumption calculated by the degree-hour method with the result of neural network model of energy consumption of the model house in Denizli, Turkey, Behrouznia et al. [75] presented an adaptive network based fuzzy inference system – fuzzy data envelopment analysis for gas consumption forecasting and analysis and Valero and

Table 1
Overview of published papers by years.

Publishing year	References
1949	Hubbert [3]
1950	Verhulst [2]
1956	Hubbert [4]
1966	Balestra and Nerlove [9]
1973	Tinic et al. [10]
1977	Berndt and Watkins [11]
1981	Beierlein et al. [76]
1983	Piggott [12]
1987	Herbert et al. [13], Herbert [14]
1988	Werbos [15]
1991	Liu and Lin [16],
1994	Lee and Singh [17], Brown et al. [18]
1996	Nagy [19], Brown and Iftekhar [20], Smith et al. [21], Suykens et al. [22], Bartels et al. [23]
1997	Sailor and Munoz [24], Al-Jarri and Startzman [5]
1999	Khotanzad and Elragal [25]
2000	Khotanzad et al. [26], Durmayaz et al.[74], Al-Fattah and Startzman [27]
2001	Gumrah et al. [28]
2002	Tahat et al. [29]
2003	Siemek et al. [30], Sarak and Satman [31]
2004	Gorucu et al. [32], Cho et al. [33], Gorucu and Gumrah [34], Aras and Aras [35], Gil and Deferrari [36], Imam et al. [37], Elragal [38], Cavallo [8]
2005	Gutierrez et al. [39], Viet and Mandziuk [40], Thaler et al. [41], Pelikan and Simunek [42]
2006	Musilek et al. [43], Gelo [78]
2007	Vondracek et al. [44], Potocnik et al. [45], Huntington [46], Sanchez-Ubeda and Berzosa [47], Timmer and Lamb [48], Potocnik et al. [49]
2008	Brabec et al. [50], Potocnik et al. [51], Kizilaslan and Karlik [52], Aydinalp-Koksal and Ugursal [53], Aras [54], Simunek and Pelikan [55], Jiang et al. [56]
2009	Brabec et al. [57,58], Kizilaslan and Karlik [59], Yoo et al. [60], Ma and Wu [61], Reynolds and Kolodziej [62], Tonkovic et al. [63], Xie and Li [64], Chen et al. [65], Maggio and Cacciola [6]
2010	Azadeh et al. [66], Ma and Li [67], Li et al. [68], Xu and Wang [69], Forouzanfar et al. [70], Erdogdu [71], Toksari [72], Dombayci [73], Behrouznia et al. [75], Valero and Valero [7]

Table 2
Overview of published papers by applied area.

Applied area	References
World level forecasting, world regions and organizations	Hubbert [3,4], Al-Jarri and Startzman [5], Al-Fattah and Startzman [27], Imam et al. [37], Maggio and Cacciola [6], Valero and Valero [7], Behrouznia et al. [75]
National level forecasting	Sanchez-Ubeda and Berzosa [47], Hubert [3,4], Suykens et al. [22] Siemek et al. [30], Gutierrez et al. [39], Huntington [46], Aydinalp-Koksal and Ugursal [53], Ma and Wu [61], Reynolds and Kolodziej [62], Xie and Li [64], Chen et al. [65], Azadeh et al. [66], Ma and Li [67], Li et al. [68], Xu and Wang [69], Erdogdu [71], Aras and Aras [35], Liu and Lin [16], Toksari [72], Nagy [19], Herbert [14], Herbert et al. [13], Aras [54], Forouzanfar et al. [70], Sarak and Satman [31]
Regional level forecasting	Beierlein et al. [76], Sailor and Munoz [24], Jiang et al. [56], Bartels et al. [23], Berndt and Watkins [11]
Gas distribution system, city area	Piggott [12], Brown et al. [18], Brown and Iftekhar [20], Smith et al. [21], Khotanzad and Elragal [25], Khotanzad et al. [26], Durmayaz et al.[74], Gumrah et al. [28], Gorucu et al. [32], Gorucu and Gumrah [34], Gil and Deferrari [36], Viet and Mandziuk [40], Thaler et al. [41], Musilek et al. [43], Gelo [78], Potocnik et al. [45,49,51] Timmer and Lamb [48], Kizilaslan and Karlik [52,59], Tonkovic et al. [63], Yoo et al. [60]
Individual customers level	Lee and Singh [17], Vondracek et al. [44], Brabec et al. [50,57]

Table 3
Overview of published papers by forecasting horizon.

Forecasting horizon	References
Annual basis	Hubbert [3,4], Berndt and Watkins [11], Al-Jarri and Startzman [5], Al-Fattah and Startzman [27], Durmayaz et al. [74], Sarak and Satman [31], Siemek et al. [30], Cavallo [8], Gorucu and Gumrah [34], Imam et al. [37], Gutierrez et al. [39], Huntington [46], Aydinalp-Koksal and Ugursal [53], Jiang et al. [56], Chen et al. [65], Ma and Wu [61], Maggio and Cacciola [6], Reynolds and Kolodziej [62], Xie and Li [64], Erdogdu [71], Forouzanfar et al. [70], Li et al. [68], Ma and Li [67], Toksari [72], Valero and Valero [7], Behrouznia et al. [75] and Xu and Wang [69]
Monthly basis	Herbert et al. [13], Herbert [14], Liu and Lin [16], Suykens et al. [22], Sailor and Munoz [24], Aras and Aras [35], Gelo [78], Timmer and Lamb [48], Aras [54], Kizilaslan and Karlik [59], Yoo et al. [60]
Daily basis	Brown et al. [18], Brown and Iftekhar [20], Khotanzad and Elragal [25], Khotanzad et al. [26], Gumrah et al. [28], Turkey, Elragal [25], Musilek et al. [43], Potocnik et al. [45], Vondracek et al. [44], Brabec et al. [50], Kizilaslan and Karlik [52], Azadeh et al. [66]
Hourly basis	Thaler et al. [41], Dombayci [73]
Combined forecasting horizons (hourly and daily)	Potocnik et al. [49,51], Tonkovic et al. [63]
Combined forecasting horizons (hourly, daily, weekly and annual)	Brabec et al. [57]
Combined forecasting horizons (daily and weekly)	Piggott [12]
Combined forecasting horizons (daily, monthly and annual)	Sanchez-Ubeda and Berzosa [47], Gil and Deferrari [36]
Combined forecasting horizons (daily, weekly and four weekly)	Viet and Mandziuk [40]

Table 4
Overview of published papers by used natural gas consumption data.

Basic input data	References
Annual consumption data	Hubbert [3,4], Maggio and Cacciola [6], Siemek et al. [30], Xu and Wang [69], Ma and Wu [61], Chen et al. [65], Gutierrez et al. [39], Forouzanfar et al. [70], Reynolds and Kolodziej [62], Ma and Li [67], Sarak and Satman [31], Bartels et al. [23], Huntington [46], Behrouznia et al. [75]
Monthly consumption data	Herbert [14], Herbert et al. [13], Liu and Lin [16], Suykens et al. [22], Sailor and Munoz [24], Aras and Aras [35], Gil and Deferrari [36], Gelo [78], Timmer and Lamb [48], Aydinalp-Koksal and Ugursal [53], Kizilaslan and Karlik [59]
Daily consumption data	Brown et al. [18], Brown and Iftekhar [20], Khotanzad and Elragal [25], Khotanzad et al. [26], Gumrah et al. [28], Viet and Mandziuk [40], Musilek et al. [43], Sanchez-Ubeda and Berzosa [47], Kizilaslan and Karlik [52], Brabec et al. [50,58], Azadeh et al. [66]
Hourly consumption data	Thaler et al. [41], Potocnik et al. [45,49,51], Brabec et al. [57], Tonkovic et al. [63]

Valero [7] showed how thermodynamics and the exergy analysis in particular can help to assess the degradation degree of earth's mineral resources. Tables 1–6.

3. Applied area

Forecasting of natural gas consumption was investigated in several different areas, on the world level, state level, regional or distributional level, separate sectors inside distribution level and finally on individual customer level.

Prediction of natural gas production, as a part of his research on nuclear energy and energy from fossil fuels, on the world and national level (USA), was investigated by Hubbert [3,4]. He tried to forecast the future oil and natural gas production, both in the world and in the USA, by establishing Hubert curve theory based on normal distribution curve. Based on Hubbert research, Al-Jarri and Startzman [5] forecasted the world future supply and demand of crude oil and natural gas liquids up to year 2050. In their research they also divided the world in regions (North America, Middle East, Africa, Far East, etc.) and predicted their future production–demand ratio. Al-Fattah and Startzman [27] discovered in their previous studies that the conventional Hubbert model with one complete production cycle is not appropriate to forecast gas-production trends for most gas-producing countries, so they developed a 'multicyclic Hubbert' approach that accurately models the gas-production history of each gas-producing country, and models for all countries were then used to forecast the future production of natural gas worldwide. They also

Table 5
Examples of various additional input data.

Model type	Additional input data	References
Annual forecasting model	Estimation of fossil fuels reserve	Hubbert [3,4], Maggio and Cacciola [6]
	Ratio oil/natural gas in known wells	Hubbert [3,4]
	Complex institutional influentces (for example drastically changes of laws and rules etc.)	Reynolds and Kolodziej [62],
	GDP (gross domestic product)	Ma and Li [67], Behrouznia et al. [75], Huntington [46],
	HDD (heating degree-days)	Sarak and Satman [31], Huntington [46]
	Number of residences in cities	Sarak and Satman [31]
	Bottled gas consumption	Bartels et al. [23]
	Number of rooms	Bartels et al. [23]
	Annual household income	Bartels et al. [23]
	Fossil fuel consumption	Huntington [46]
	Natural gas price	Huntington [46]
	Fuel and power price	Huntington [46]
	Coal price	Huntington [46]
	Petroleum product price	Huntington [46]
Monthly forecasting model	HDD (heating degree-days)	Herbert [14], Herbert et al. [13]
	CDD (cooling degree-days)	Herbert [14]
	Natural gas price	Herbert [14], Herbert et al. [13], Liu and Lin [16], Gelo [78], Aydinalp-Koksal and Ugursal [53]
	Indeks of income	Herbert [14]
	Price of residual fuel oil	Herbert et al. [13]
	Temperature	Liu and Lin [16], Suykens et al. [22], Sailor and Munoz [24], Aras and Aras [35], Gil and Deferrari [36], Gelo [78], Timmer and Lamb [48], Aydinalp-Koksal and Ugursal [53], Kizilaslan and Karlik [59]
	Number of clients	Suykens et al. [22]
	Oil price	Suykens et al. [22]
	Relative humidity	Sailor and Munoz [24]
	Wind speed	Sailor and Munoz [24]
	Day of week	Gil and Deferrari [36], Aydinalp-Koksal and Ugursal [53]
	Holliday or working day variable	Gil and Deferrari [36]
	Monthly average natural gas consumption per customer	Gelo [78]
	Average salary	Gelo [78]
	Household income	Aydinalp-Koksal and Ugursal [53]
	Size of heated space	Aydinalp-Koksal and Ugursal [53]
	Number of tenants	Aydinalp-Koksal and Ugursal [53]
	Efficiency of heating boiler	Aydinalp-Koksal and Ugursal [53]
	Age of heating boiler	Aydinalp-Koksal and Ugursal [53]
Daily forecasting model	HDD (heating degree-day)	Brown et al. [18], Brown and Iftekhar [20], Gumrah et al. [28]
	Temperature	Brown et al. [18], Brown and Iftekhar [20], Viet and Mandziuk [40], Musilek et al. [43], Brabec et al. [50,58]
	Wind speed	Brown et al. [18], Brown and Iftekhar [20]
	Day of the week	Brown et al. [18], Brown and Iftekhar [20], Khotanzad and Elragal [25], Khotanzad et al. [26], Musilek et al. [43], Sanchez-Ubeda and Berzosa [47], Kizilaslan and Karlik [52], Brabec et al. [50,58], Azadeh et al. [66]
	Day of the year	Brown et al. [18], Brown and Iftekhar [20], Musilek et al. [43], Kizilaslan and Karlik [52]
	Month of the year	Kizilaslan and Karlik [52]
	Yesterday consumption	Khotanzad and Elragal [25], Khotanzad et al. [26], Azadeh et al. [66]
	Day before yesterday consumption	Khotanzad and Elragal [25], Khotanzad et al. [26], Azadeh et al. [66]
	Yesterday temperature	Khotanzad and Elragal [25], Khotanzad et al. [26]
	Day before yesterday temperature	Khotanzad and Elragal [25], Khotanzad et al. [26]
	Yesterday wind speed	Khotanzad and Elragal [25], Khotanzad et al. [26]
	Day before yesterday wind speed	Khotanzad and Elragal [25], Khotanzad et al. [26]
	Working days – weekend days	Viet and Mandziuk [40], Sanchez-Ubeda and Berzosa [47], Brabec et al. [57]
	Holidays	Musilek et al. [43], Sanchez-Ubeda and Berzosa [47]
	Expert estimates of start/end heating season	Musilek et al. [43]
	Daily minimum temperature	Sanchez-Ubeda and Berzosa [47], Kizilaslan and Karlik [52]
	Daily maximum temperature	Sanchez-Ubeda and Berzosa [47], Kizilaslan and Karlik [52]
	Total number of customers	Kizilaslan and Karlik [52]
	Consumption of the same day in previous year	Azadeh et al. [66]
Hourly forecasting model	Temperature	Thaler et al. [41], Potocnik et al. [45,49,51], Brabec et al. [57], Tonkovic et al. [63]
	Wind speed	Thaler et al. [41], Tonkovic et al. [63]
	Season	Thaler et al. [41], Potocnik et al. [45,49,51]
	Day of the week	Thaler et al. [41], Potocnik et al. [45,49,51], Brabec et al. [57], Tonkovic et al. [63]
	Holidays	Potocnik et al. [45,49,51]

developed and analyzed supply models for some organizations like Organization of Petroleum Exporting Countries (OPEC), the Organization for Economic Cooperation and Development (OECD), the European Union (EU), and the International Energy Agency (IEA). Imam et al. [37] also used the 'multicyclic Hubbert' curve to forecast the world natural gas production. Maggio and Cacciola [6] also proposed a model based on a variant of the well known Hubbert curve, with several different scenarios, to determine the peak and the behavior of the world crude oil and NGL production. Valero and Valero [7] showed how thermodynamics and the exergy analysis in particular can help to assess the degradation degree of the earth's mineral resources, and among others, they applied Hubbert

Table 6
Overview of used forecasting tools.

Forecasting tools	References
Hubbert curve model	Hubbert [3,4], Al-Jarri and Startzman [5], Al-Fattah and Startzman [27], Siemek et al. [30], Cavallo [8], Imam et al. [37], Reynolds and Kolodziej [62], Maggio and Cacciola [6] and Valero and Valero [7]
Statistical models	Balestra and Nerlove [9], Beierlein et al. [76], Piggott [12], Herbert et al. [13], Herbert [14], Liu and Lin [16], Erdogdu [71], Brabec et al. [50], Lee and Singh [17], Sailor and Munoz [24], Aras and Aras [35], Gorucu and Gumrah [34], Huntington [46], Timmer and Lamb [48], Sanchez-Ubeda and Berzosa [47], Vondracek et al. [44], Brabec et al. [57,58], Yoo et al. [60], Behrouznia et al. [75], Azadeh et al. [66]
Artificial neural networks	Werbos [15], Brown et al. [18], Brown and Iftekhar [20], Suykens et al. [22], Khotanzad and Elragal [25], Khotanzad et al. [26], Gorucu et al. [32], Elragal [38], Khotanzad and Elragal [25], Khotanzad et al. [26], Viet and Mandziuk [40], Musilek et al. [43], Kizilaslan and Karlik [52,59], Tonkovic et al. [63], Dombayci [73]
Grey prediction model	Xie and Li [64], Ma and Wu [61], Chen et al. [65], Ma and Li [67], Xu and Wang [69]
Conditional demand analysis	Bartels et al. [23], Aydinalp-Koksal and Ugursal [53]
Econometric model	Berndt and Watkins [11], Nagy [19], Gelo [78]
Mathematical model	Gil and Deferrari [36], Simunek and Pelikan [55]
Expert system	Smith et al. [21]
Stochastic Gompertz innovation diffusion model	Gutierrez et al. [39]
Dynamical system model	Li et al. [68]
Simulated annealing	Toksari [72]

peak model to the natural gas world exergy consumption. Behrouznia et al. [75] presented an adaptive network based fuzzy inference system for predicting natural gas demand for South America.

Several authors discussed prediction of natural gas consumption on national level like Sanchez-Ubeda and Berzosa [47], who presented a novel prediction model that provides forecasting the end-use industrial consumption in Spain, in a medium-term horizon (1–3 years) with a very high resolution (days) based on a decomposition approach. Also in his research, Hubert [3,4] among others forecasted the level of natural gas consumption in the USA. Suykens et al. [22] proposed neural network model for the gas consumption in Belgium, while Siemek et al. [30] used adaptation of Hubbert model to predict natural gas consumption in Poland for forty years ahead, Gutierrez et al. [39] examined the possibilities of using a Gompertz-type innovation diffusion process as a stochastic growth model for forecasting natural gas consumption in Spain, Huntington [46] developed statistical model of industrial natural gas consumption in the United States, Aydinalp-Koksal and Ugursal [53] investigated use of conditional demand analysis (CDA) method to model the residential end-use energy consumption on the national level in Canada, Ma and Wu [61] forecasted natural gas consumption and production in China, Reynolds and Kolodziej [62] used different institutional influence on the US gas market in order to explain multi-cycle Hubbert curve, Xie and Li [64] forecasted natural gas consumption in China using Grey modeling optimized by Genetic algorithm, Chen et al. [65] presented method, based on genetic algorithms, to forecast China natural gas consumption, Azadeh et al. [66] used adaptive network-based fuzzy inference system (ANFIS) for estimation of natural gas demand in Iran, Ma and Li [67] analyzed reserves, distribution, production and utilization of natural gas resources, and predicted the future production and consumption of natural gas in China, Li et al. [68] developed a dynamical system model in order forecast natural gas consumption in the near future in China, Xu and Wang [69] forecasted China natural gas consumption using combination model, Erdogdu [71] forecasted future growth in natural gas demand in Turkey, using an ARIMA modeling, Aras and Aras [35] divided year into heating and non-heating season and used Degree Day method for forecasting residential monthly natural gas consumption in Turkey, Liu and Lin [16] forecasted consumption of natural gas in Taiwan within residential sector, Toksari [72] presented a heuristic approach to estimate Turkey's natural gas demand, Nagy [19] estimated the demand for natural gas in Kuwait, Herbert [14] analyzed monthly sales of natural gas to residential customers in the United States, Herbert et al. [13] evaluated aggregate monthly industrial demand for natural gas in the United States, Aras [54] forecasted short-term demand of natural gas in residential sector in Turkey, Forouzanfar et al. [70] forecasted the natural gas consumption for residential and commercial sectors in Iran and Sarak and Satman [31] used the degree-day method to estimate residential heating natural gas consumption in Turkey.

Beierlein et al. [76] investigated and estimated demand for electricity and natural gas for the northeastern United States. Sailor and Munoz [24] developed a methodology for assessing the sensitivity of electrical and natural gas consumption to climate on regional scales, Jiang et al. [56], focused their research on three regions: Beijing, Guangdong, and Shanghai in order to identify some of the important factors that might drive natural gas consumption in key demand areas in China, Bartels et al. [23] used statistical method of conditional demand analysis (CDA) to estimate the regional end-use consumption of natural gas in Australia, Berndt and Watkins [11] estimated natural gas demand in residential and commercial market sectors in British Columbia and Ontario.

In order to forecast daily and weekly gas demand in British Gas distribution system, Piggott [12] used Box–Jenkins approach, Brown et al. [18] predicted gas consumption on a daily basis for a region in metropolitan Milwaukee, Brown and Iftekhar [20] predicted daily gas consumption in two regions in Wisconsin served by Wisconsin Gas Company, Smith et al. [21] predicted gas demands by regional gas company, Khotanzad and Elragal [25] used combination of artificial neural networks to predict natural gas consumption of four local distribution company, Khotanzad et al. [26] expanded work on predicting of natural gas consumption of six local distribution companies, Durmayaz et al.[74] used degree-hour method to estimate seasonal natural gas consumption in Istanbul, Gumrah et al. [28] used degree-day concept (DD) for predicting gas demand in the city of Ankara, Gorucu et al. [32] forecasted natural gas consumption in the city of Ankara, Gorucu and Gumrah [34] developed statistical multivariable regression analysis to forecast gas consumption for the capital city of Ankara, Gil and Deferrari [36] presented model for predicting the residential and commercial natural gas consumption in Greater Buenos Aires region, Viet and Mandziuk [40] analyzed prediction of natural gas consumption in two different regions in Poland, Thaler et al. [41] described empirical model for prediction of energy consumption in a typical distribution systems in Slovenia, Musilek et al. [43] solved the problem of seasonal dependency forecasting gas load in distribution system, Gelo [78] analyzed modeling of average gas consumption in Zagreb gas distribution system, Potocnik et al. [45] proposed a strategy to estimate forecasting risk in a typical distribution systems in Slovenia, Timmer and Lamb [48] quantified relations between winter temperature and residential gas consumption for the eastern regions of the USA, Potocnik et al. [49] demonstrated forecasting approach for Slovenian natural gas distribution company, Potocnik et al. [51] discussed practical considerations on building forecasting applications for predicting natural gas consumption in distribution companies in Slovenia, Kizilaslan and Karlik [52] forecasted natural gas consumption in Istanbul, Kizilaslan and Karlik [59] forecasted natural gas consumption for residential and commercial consumers in Istanbul, separated on Anatolian and Europian sides, Tonkovic et al. [63] created prediction model of natural gas consumption in Osijek, Yoo et al. [60] estimated households' demand for natural gas in Seoul.

At last, Lee and Singh [17] investigated individual consumption of natural gas and electricity in households, Vondracek et al. [44] presented a statistical approach to natural gas consumption estimation of individual residential and small commercial customers, Brabec et al. predicted daily natural gas consumption on the level of individual customers [50] and continued their work on statistical model for construction and application of standardized load profiles for individual customers [57].

4. Forecasting horizon

In the published papers, forecasting gas consumption, production or demand was investigated on several different time horizons. Large number of researchers forecasted gas consumption, production or demand on annual level like Hubbert [3,4] who investigated life circle of fossil fuel fields and forecasted their life circle several decades ahead, Berndt and Watkins [11], Al-Jarri and Startzman [5], Al-Fattah and Startzman [27] forecasted the world's annual supply of conventional natural gas, Durmayaz et al. [74] estimated seasonal natural gas consumption in Istanbul, Sarak and Satman [31], who estimated annual residential heating natural gas consumption in Turkey, Siemek et al. [30], who investigated Poland's annual natural gas consumption, Cavallo [8], Gorucu and Gumrah [34] forecasted annual gas consumption for the capital city of Ankara, Imam et al. [37], Gutierrez et al. [39], who examined the annual consumption of natural gas in Spain, Huntington [46], who developed statistical model for annual consumption of industrial natural gas in United States, Aydinalp-Koksal and Ugursal [53], who investigated annual residential end-use energy consumption, Jiang et al. [56] forecasted annual natural gas consumption in key demand areas in China, Chen et al. [65] forecasted China's annual natural gas consumption, Ma and Wu [61] forecasted annual natural gas consumption and production in China from 2008 till 2015, Maggio and Cacciola [6], Reynolds and Kolodziej [62], Xie and Li [64], Erdogdu [71], Forouzanfar et al. [70], who forecasted annual natural gas consumption for residential and commercial sectors in Iran, Li et al. [68], Ma and Li [67], Toksari [72], Valero and Valero [7], Behrouznia et al. [75] and Xu and Wang [69], who estimated the future natural gas consumption in China from 2009 to 2015.

There is also a number of authors who reported on forecasting monthly gas consumption like Herbert et al. [13], who evaluated aggregate monthly industrial demand for natural gas in the USA, Herbert [14], who analyzed monthly sales of natural gas to residential customers in the USA to estimate monthly and annual natural gas deliveries, Liu and Lin [16] who created monthly and quarterly model for forecasting residential consumption of natural gas in Taiwan, Suykens et al. [22] who proposed a model for monthly gas consumption in Belgium, Sailor and Munoz [24], Aras and Aras [35], who forecasted residential monthly natural gas consumption, Gelo [78], who analyzed monthly average gas consumption in Zagreb, Timmer and Lamb [48], Aras [54], Kizilaslan and Karlik [59], who presented a forecasting model for monthly gas consumption for residential and commercial consumers in Istanbul and Yoo et al. [60], who estimated households' monthly demand function for natural gas in Seoul.

Daily models for forecasting gas consumption were reported by Brown et al. [18], who developed neural network models on a daily basis, Brown and Iftekhar [20], who predicted the daily gas consumption in two regions in Wisconsin, Khotanzad and Elragal [25], who used combination of artificial neural networks for one day ahead forecasts, Khotanzad et al. [26], Gumrah et al. [28], who used degree-day concept (DD) for modeling of gas demand in Ankara, Turkey, Elragal [25], Musilek et al. [43], Potocnik et al. [45], who estimated forecasting risk on daily basis, Vondracek et al. [44], who presented daily natural gas consumption estimation of individual residential and small commercial customers from monthly meter reading, Brabec et al. [50], who predicted daily natural gas consumption on the level of individual customers, Kizilaslan and Karlik [52] who forecasted Istanbul's natural gas energy model on a daily and weekly basis and Azadeh et al. [66], who estimated daily natural gas demand in Iran.

Forecasting gas consumption on hourly scale was reported by Thaler et al. [41], who described empirical model for prediction of hourly gas consumption in a typical distribution system in Slovenia and Dombayci [73], who compared hourly heating energy consumption calculated by degree-hour method with the result of neural network model of energy consumption of the model house in Denizli, Turkey.

Several combined forecasting horizons are also reported in literature, where the author predicted hourly and daily gas consumption in the same paper, like Potocnik et al. [49], who demonstrated an energy forecasting approach where the energy consumption cycles are analyzed on hourly and daily basis. Some authors even combined hourly, daily, weekly and annual forecasting horizon like Brabec et al. [57] who worked on statistical model for construction and application of standardized load profiles for individual customers. Piggott [12] combined daily and weekly, Sanchez-Ubeda and Berzosa [47] and Gil and Deferrari [36] combined daily, monthly and annual, Viet and Mandziuk [40] used daily data and analyzed several approaches to predict natural gas consumption in two different regions in Poland on daily, weekly and four weekly basis.

5. Data

Forecasting of gas consumption was investigated in different areas and on different forecasting horizons which usually have different approach in solving forecasting problem so different input data have been used. Because of complexity, various kinds of additional data were used in solving the same kind of problem.

In his works Hubbert [3,4] used fossil fuels annual statistics of their production and estimates of ultimate reserves. Because of their orientation on Hubbert curve model, the same kind of data were used by Maggio and Cacciola [6]. Whole line of authors who investigated consumption on forecasting horizon of several or more years and on national level, used annual consumption data as base input data, like Siemek et al. [30], Xu and Wang [69], Ma and Wu [61], Chen et al. [65], Gutierrez et al. [39], Forouzanfar et al. [70]. Besides the basic input data, some authors who discussed previously mentioned forecasting problem also used some other data like Reynolds and Kolodziej [62] who, besides usual data used in the Hubbert curve model, also used and discussed various complex institutional influences on Hubbert curve model. Ma and Li [67] in their Grey model analysis of the supply–demand status of China, besides annual consumption data, also used gross domestic product (GDP) as input data. Sarak and Satman,[31] besides annual consumption data for residential sector, used annual heating degree days and number of residents in the cities. Some authors like Bartels et al. [23] used even detailed data because National energy survey gave them an opportunity to analyze gas consumption influenced by bottled gas consumption, number of usual residents, number of rooms, annual household income etc. In his paper Huntington [46] investigated industrial gas consumption, and besides annual gas consumption data, as input variables he also used fossil fuel consumption, heating (Heating Degree Days, HDDs), cooling (Cooling Degree Days, CDDs), number of econometric variables like FPC price controls (Texas industrial gas price divided by US wellhead gas price, if ratio >1.5), natural gas price, natural gas price for industrial customers, fuel and power price, distillate fuel price, residual fuel price, petroleum product price, coal price, GDP price deflator, manufacturing output, manufacturing energy-weighted output, manufacturing capacity utilization, and industrial capacity utilization. Behrouznia et al. [75] used the annuall consumption data (1980–2007) for South America, GDP and population data in order to forecast future gas demand till 2015.

Monthly consumption data were used as basic input data in various papers in which monthly based forecasting horizon was investigated. Herbert [14] used past monthly deliveries of natural gas with the combination of HDD, CDD, price and index of income in order to estimate monthly and annual natural gas deliveries to residential customers. Herbert et al. [13] used monthly industrial demand for natural gas, HDD, price of natural gas and price of residual fuel oil in order to estimate aggregate monthly industrial demand for natural gas in USA. Liu and Lin [16] used monthly natural gas consumption of residential sector, average monthly temperature and monthly price of natural gas in order to model and forecast monthly and quarterly gas consumption of residential sector in Taiwan. Suykens et al. [22] used monthly consumption by domestic residential clients and by industry, number of domestic clients, temperature, and oil price in order to estimate monthly gas consumption in Belgium. Sailor and Munoz [24] used monthly natural gas consumption of residential and commercial customers, temperature, relative humidity and wind speed in order to determine the sensitivity of monthly natural gas consumption to climate on regional scales. Aras and Aras [35] used monthly amounts of natural gas consumption in residences and daily mean temperatures in order to model and forecast future natural gas consumption in residences. Gil and Deferrari [36] used monthly natural gas consumption, daily mean temperature, day of the week, holiday or working day variable in order to forecast the future natural gas consumption in residential and commercial sector. In addition, they presented a novel procedure to obtain the distribution of daily consumption from the monthly consumption and HDD for the analyzed area. Gelo [78] used monthly average gas consumption per customer, average monthly air temperature, average salary and gas price. Timmer and Lamb [48] used monthly natural gas consumption data of residential sector in relation to temperature in order to determine the relations between temperature and residential natural gas consumption. Detailed analysis of gas consumption, among other types of energy consumption, in residential sector was conducted by Aydinalp-Koksal and Ugursal [53]. They used monthly natural gas consumption data, temperature data, day of the week data, price, household income, size of heated space, number of tenants, efficiency of heating boiler, age of heating boiler, size of area of residence, variable if there is programmable thermostat, age of heating system, etc. in order to model the residential end-use energy consumption on the national level. Monthly gas consumption was basic data in Kizilaslan and Karlik [59]. With additional temperature data they used seven different neural network training algorithms in order to show possibility of artificial neural networks utilization for forecasting monthly natural gas consumption.

Brown et al. [18] used daily consumption data in order to develop feed-forward network models to predict gas consumption on a daily basis. Besides the daily consumption data the authors also used weather data (average daily temperature for calculating HDD and wind speed) and calendar data (day of week, day of year). Brown and Iftekhar [20] used the same shape of input data as previous paper but for the period 21-December-1989 till 29-March-1994. Khotanzad and Elragal [25] in their paper used the daily consumption for the past two days, daily average temperature for the past two days, daily average wind speed for the past two days and day of the week as input in their Neural network models in order to forecast one day ahead. Khotanzad et al. [26] used the same shape of input data as the previous paper (daily consumption, temperature, wind speed and day of the week) in order to forecast one day ahead gas consumption. Gumrah et al. [28] used the daily consumption and DD (degree day). Viet and Mandziuk [40] used daily consumption, daily average temperature and calendar data (working days, weekends) in order to forecast gas consumption one day ahead, one week ahead and four weeks ahead. Musilek et al. [43] used daily consumption, daily mean temperature (five days before), calendar data (day of the week, holidays, day of the year) and expert estimates of start/end heating season in order to forecast one day ahead consumption. Sanchez-Ubeda and Berzosa [47] used daily industrial end-use gas consumption, daily minimum and maximum outdoor air temperature, calendar data (day of the week, holiday or working day, Easter and Christmas) in order to model industrial end-use natural gas consumption on daily and monthly basis three years ahead. Kizilaslan and Karlik [52] used daily consumption, daily minimum and maximum outdoor air temperature, calendar data (day of the week, day of the year, month, year) and total number of customers in order to forecast daily and weekly gas consumption in Istanbul, Turkey. Brabec et al. [50] used daily consumption data of 62 individual customers and in combination with daily average temperature and day of the week they made the individual gas consumption model for each customer. Brabec et al. [58] used daily consumption data, temperature and calendar data for their research in statistical calibration of the natural gas consumption model. Azadeh et al. [66] used Iran's daily consumption data and calendar data (day of the week) in order to train and test the ANFIS models for daily forecasting model.

Hourly consumption data were usually used as basic input data in those papers in which hourly and daily based forecasting horizon was investigated. Thaler et al. [41] investigated the prediction of energy consumption and risk of excess energy demand in distribution system by using hourly gas consumption data from a typical Slovenian city. The authors explained that, besides natural gas data, in such research weather data (temperature, wind speed, solar radiation, etc.) and calendar data (day in the week, season, etc.) could also be used. Potocnik et al. in their research [45,49, 51] used hourly consumption data, temperature, calendar data (winter, summer, day of the week, holidays) in order to forecast hourly and daily natural gas consumption. Brabec et al. [57] used hourly consumption data, temperature and calendar data (weekday, weekend) for an individual customer in order to create standardized load profiles of gas consumption. Tonkovic et al. [63] used hourly consumption data, weather data (temperature and wind speed) and calendar data (day of the week) in order to forecast gas consumption in distribution system in Osijek, Croatia.

6. Forecasting tools

In the published papers, forecasting natural gas consumption, demand and production were investigated by various forecasting tools and techniques. Among the first tools established for forecasting natural gas consumption is the Hubbert curve model. In his papers Hubbert [3,4] investigated annual statistics of fossil fuels production, and after having plotted production over time curves, he noticed that the curves had similar characteristics and strong family resemblance among them: each curve starts slowly and then rises more steeply until finally it reaches an inflection point after which it becomes concave downward. His model is based on two basic considerations:

1. For any production curve of finite resource of fixed amount, two points on the curve are known on the outset, namely that $t = 0$ and again on $t = \infty$. The production rate will be zero at the beginning, whereas at the end of exploitation, when the resource is exhausted, with one or several maxima in between.
2. The second consideration arises from the fundamental theorem of the integral calculus: if there is production curve plotted against time on an arithmetical scale $P = dQ/dt$, where dQ is quantity of resource produced in time dt, then the total area under the curve, on the graph of production-versus-time, will represent ultimate production of any exhaustible source.

After these considerations, he estimated ultimate reserves of fossil fuels and then forecasted the future rates of production. The same or modified model was used in Al-Jarri and Startzman [5], Al-Fattah and Startzman [27], Siemek et al. [30], Cavallo [8], Imam et al. [37], Reynolds and Kolodziej [62], Maggio and Cacciola [6] and Valero and Valero [7].

Statistical models for natural gas consumption have been developed and used since the 1960s and since that time various statistical models have been commonly used as forecasting tool in the past researches. Among the first reported, Balestra and Nerlove [9] used statistical tools and time series data in forecasting demand for natural gas. In order to estimate the demand for electricity and natural gas in northeastern United States, Beierlein et al. [76] used seemingly unrelated regression estimation. Piggott [12] used Box–Jenkins modeling in time series analysis. Herbert et al. [13] used regression analysis, whereas regression analysis, residual analysis and linear regression equation were used in Herbert [14]. ARIMA models were reported in Liu and Lin [16] and Erdogdu [71]. Liu and Lin [16] employed Linear transfer function method (LTF method) and Cros correlation function method (CCF method). Brabec et al. [50] used NLME (Nonlinear mixed effects model) compared with ARIMAX (auto-regressive integrated moving average with eXtra/eXternal process) and ARX (auto-regressive with exogenous inputs). Lee and Singh [17] used modified multiple regression technique, generalized Tobit model, Chow test, Hausman test, White test and estimation by the nearest neighbor rule. Linear least-squares regression method (using two sets of independent variables–primitive variables) with degree-day model was reported in Sailor and Munoz [24]. In forecasting residential natural gas, Aras and Aras [35] investigated single and separate (heating and non-heating season) models. They created three first order autoregressive time series models in which the deterministic component is a periodic function of time and degree-day values. Gorucu and Gumrah [34] in their evaluation and forecasting gas consumption used multivariable regression analysis. With the use of autoregressive distributed lag (ADL) and several tests (*F*-test, Jarque–Bera test, Breusch–Godfrey test, Chow test) Huntington [46] investigated industrial natural gas consumption. Timmer and Lamb [48] used linear model with days below percentile (DBP) and Heating Degree Days (HDDs) in determining relations between temperature and residential natural gas consumption. Sanchez-Ubeda and Berzosa [47] used novel statistical decomposition model, iterative algorithm improved by minimizing mean square error (MSE). Vondracek et al. [44] used statistical nonlinear regression model with individual customer effect where parameters of the model are estimated separately for each customer segment. Brabec et al. [58] used time-varying statistical model of state-space nature, from which calibration arises as a natural way to improve original model due to various deficiencies of the original sample-only based model, possible inconsistencies between sample and the population as a whole, and/or inherently different nature of the available sample and population data. In order to create the standardized load profiles of natural gas customers, Brabec et al. [57] used semiparametric regression model with multiplicative structure which allows convenient separation of individual-specific and common time varying parts. Yoo et al. [60] used sample selection model and several tests (*Z*-test for non-response bias, likelihood-ratio test and *t*-test for sample selection bias) in order to estimate residential demand function for natural gas in Seoul. Adaptive network based fuzzy inference system (ANFIS) were forecasting tool in Behrouznia et al. [75] and Azadeh et al. [66]. Behrouznia et al. [75] used six different ANFIS models in order to find the best fitting one while Azadeh et al. [66] compared ANFIS model with artificial neural networks (ANN) model.

> "Artificial neural networks, originally developed to mimic basic biological neural systems – the human brain particularly, are composed of a number of interconnected simple processing elements called neurons or nodes. Each node receives an input signal which is the total "information" from other nodes or external stimuli, processes it locally through an activation or transfer function and produces a transformed output signal to other nodes or external outputs. Although each individual neuron implements its function rather slowly and imperfectly, collectively a network can perform a surprising number of tasks quite efficiently. This information processing characteristic makes ANNs a powerful computational device and able to learn from examples and then to generalize to examples never before seen. The idea of using ANNs for forecasting is not new. The first application dates back to 1964. Due to the lack of a training algorithm for general multi-layer networks at the time, the research was quite limited." [77]

After several decades of use it becomes widely used tool in forecasting. In 1988 Werbos [15] reported the use of artificial neural networks with generalization of back-propagation to a recurrent gas market. "Werbos (1974), (1988) first formulates the back-propagation and finds that ANNs trained with back-propagation outperform the traditional statistical methods such as regression and Box–Jenkins approaches."[77] Brown et al. [18] and Brown and Iftekhar [20] developed and used feed-forward artificial neural network based models to predict gas consumption and they compared it with linear regression model. Suykens et al. [22] created model for the Belgian gas consumption using static nonlinear artificial neural networks. Khotanzad and Elragal [25] used a two stage system with three different ANN forecasters in the first stage and non-linearly combined forecasters in the second stage. The first stage ANN forecasters are a multi-layer feed-forward network trained with back-propagation, multi-layer feed-forward network trained with Levenberg–Marquardt Algorithm and one-layer functional link network. These three separate forecasts are non-linearly combined using a functional link ANN combiner in the second stage. Khotanzad et al. [26] continued working on combination of artificial neural network (ANN) forecasters with application to the prediction of daily natural gas consumption. They used a two-stage system with the first stage containing two ANN forecasters, a multi-layer feed-forward ANN and a functional link ANN. The second stage consists of a combination module to mix the two individual forecasts produced in the first stage. Authors examined eight different combination algorithms which are based on: averaging, recursive least squares, fuzzy logic, feed-forward ANN, functional link ANN, temperature space approach, Karmarkar's linear programming algorithm and adaptive mixture of local experts (modular neural networks) for six different local distribution companies, in order to find the best fitting one. Gorucu et al. [32] used ANN, while Elragal [38] continued his work

[25,26] by combining ANN forecasters in the second stage using a Fuzzy-Genetic combiner and getting even better results. Viet and Mandziuk [40] used and compared several different models: naive prediction, prediction using linear and quadratic regression models, single neural network prediction module, prediction using a combination of three neural modules, prediction using three neural modules – each of which was devoted to a predefined temperature range and prediction based on a single fuzzy neural network module, each for a daily and weekly forecasting horizon. Musilek et al. [43] introduced new mixture model based on Jordan's partial recurrent NN which are used to extend the forecasting system ELVIRA, a modular system developed and used for utility load predictions in various time horizons which already contain several forecasting modules: Box–Jenkins models, Case-based reasoning (CBR) models, Rule-based system, Artificial neural networks, Decomposition time series. Kizilaslan and Karlik [52,59] used ANN with seven different algorithms: Quick propagation Algorithm, Conjugate Gradient Descent Algorithm, Quasi-Newton Algorithm, Limited Memory Quasi-Newton Algorithm, Levenberg–Marquardt Algorithm, Incremental Back-Propagation Algorithm, Batch Back-Propagation Algorithm in order to forecast daily, weekly and monthly gas consumption in Istanbul. In order to determine effect of factors they used full regression analysis. Tonkovic et al. [63] used multi-layer perceptron and radial basis function (a – logistic activation function, b – tanh activation function, c – Gaussian activation function). Dombayci [73] used feed-forward back-propagation neural network in order to compare its result with calculated value of energy consumption.

Several authors used Genetic algorithms (GA) as a useful tool in forecasting natural gas consumption like Pelikan and Simunek [42] who used GA as an optimizing tool in risk management of the natural gas consumption in order to minimize losses and maximize profits of distribution company and Aras [54] who presented an application of genetic algorithms to forecast short-term demand of natural gas in residences. The author used a genetic algorithm to estimate parameters of a multiple nonlinear regression model which mathematically represents the relationship between natural gas consumption and influential variables. Forouzanfar et al. [70] used a logistic based approach to forecast the natural gas consumption for residential and commercial sectors with the use of two different methods to estimate the logistic parameters. The first method is based on the concept of the nonlinear programming (NLP) and the second one is based on genetic algorithm (GA). Genetic algorithms are also used in other forecasting models as helpful tool, as we will see in the rest of paper.

> "Traditional first-order Grey prediction model, which is called GM(1,1) model, is a Grey dynamic prediction model, which is widely used and in some areas has made remarkable achievements. GM(1,1) model is based on first-order differential equations. Solutions of model coefficients are analyzed based on the least squares method of statistical regression analysis system. GM(1,1) prediction model is essentially do an accumulation generating operation to the original sequence, generate a sequence showed some regularity, set up a first-order linear differential equation model, and obtain the fitting curve of prediction for the system" [64].

> "This model is generally described as GM(M,N), where M is the rank of differential equation, and N is the number of variables" [61].

Xie and Li [64] used GM(1,1) optimized by Genetic algorithm in order to create natural gas consumption model. Ma and Wu [61] applied the Markov-chain to develop the GM(1,1) models to forecast the natural gas consumption and production in China and compared its results with traditional GM(1,1) applied on the same data. Chen et al. [65] used Grey model as one of the six different forecasting tools. They also used a regression model, combination models (with least squares method, with Genetic algorithm, minimum error in single fitting, "minimum the global fitting error", "minimum the square error sum") in order to find the best forecasting tool. Ma and Li [67] predicted the future production and consumption of China's natural gas by using the Generalized Weng Model and the Gray prediction model. Xu and Wang [69] used GM(1,1) as one of several different forecasting model. They also used Second order Polynomial curve model (2nd OPC), Moving average model (MA), polynomial curve and MA combination projection model (PCMACP model) and neural network model.

Bartels et al. [23] estimated the end-use consumption in Australia using conditional demand analysis model (CDA), while Aydinalp-Koksal and Ugursal [53] compared CDA model with engineering based model developed earlier (using building energy simulation program) and neural networks model.

The sum of difference between constant inside temperature of heated area and outside temperature called degree-hour, degree-day, degree-month or degree-year are often used as a helpful parameter in forecasting natural gas consumption like in Herbert [14], Herbert et al. [13], Brown et al. [18], Brown and Iftekhar [20], Dombayci [73], Aras and Aras [35], Aras [54], Sanchez-Ubeda and Berzosa [47], Timmer and Lamb [48], Huntington [46], Gil and Deferrari [36], and Sailor and Munoz [24]. Some authors like Durmayaz et al.[74], Gumrah et al. [28] and Sarak and Satman [31] even explicitly mentioned degree-hour or degree-day in title of their work.

Econometric modeling of gas consumption was used in Berndt and Watkins [11], Nagy [19] and Gelo [78], Thaler et al. [41] and Potocnik et al. [49] used empirical modeling, Jiang et al. [56] used MARKAL economic optimization model, Gil and Deferrari [36] and Simunek and Pelikan [55] created mathematical model, Smith et al. [21] used forecasting system based on expert system, Gutierrez et al. [39] used stochastic Gompertz innovation diffusion model, Li et al. [68] used dynamical system model based on the research accomplishments by the predecessors whereas Toksari [72] used simulated annealing (SA) natural gas demand estimation model with economical indicators.

7. Conclusion

In this paper a review of the current state of forecasting natural gas consumption from the beginning to the end of 2010 has been presented. The author tried to be comprehensive but still to show the most important lines of natural gas forecasting research area. It is obvious that this area is developing because from 1949 to 2004, in 55 years there have been 29 published papers, whereas from 2004 to 2010, in last 7 years there have been 47 published papers. Using the previous text the author has divided the published papers in the area of forecasting natural gas consumption into several groups according to:

- Forecasting area:
  - World level.
  - National level.
  - Regional level.
  - Gas distribution system level.
  - Individual customer level.
- Forecasting horizon:
  - Hourly.
  - Daily.
  - Monthly.
  - Annual.
  - Combined.

- Used gas consumption data:
  - Hourly.
  - Daily.
  - Monthly.
  - Annual.
- Forecasting tools:
  - Hubbert model.
  - Grey model.
  - Statistical model.
  - Econometric model.
  - Neural network model.
  - Mathematical model.
  - Combination model.

In the past decade plenty of combination tools could be seen in order to get as good as possible results (Grey model based on Genetic algorithm, neural networks with fuzzy genetic, combination of neural networks, etc.) which will probably continue in future, together with individualization of forecasting problem like in Brabec et al. [57]. In the future we will probably see further development of Hubert and Grey model as main tools on the global forecasting area (world, continental and partly national level). On the lower forecasting area level (national, regional, gas distribution system, gas distribution sector and individual) optimizing tool combined with classic forecasting tools will probably become main direction in further research. On the individual level we could expect further detailed research in modeling natural gas consumption with the mentioned combined tools and detailed input data.

Acknowledgments

The author is grateful to Nataša Šarlija, Marijana Zekić-Sušac, Goran Šimunović, Snežana Simić and Zoran Podobnik for their constructive and helpful comments, discussions and feedback on this work. The author would like to acknowledge the anonymous reviewers of this paper, who have helped to notably enrich this study.

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Glossary

ADL: autoregressive distributed lag
ANFIS: adaptive network-based fuzzy inference system
ANN: artificial neural network
ARIMA: autoregressive integrated moving average
ARIMAX: auto-regressive integrated moving average with eXtra/eXternal process
ARX: auto-regressive with exogenous inputs
CCF: Cros correlation function
CDA: conditional demand analysis
CDD: cooling degree days
DBP: days below percentile
DD: degree-days
EU: European Union
GDP: gross domestic product
GM: Grey model
HDD: heating degree-days
HDH: heating degree-hours
IEA: international energy agency
LTF: linear transfer function
NLME: nonlinear mixed effects model
NN: neural network
OECD: Organization for Economic Cooperation and Development
OPEC: Organization of Petroleum Exporting Countries
PCMACP: Polynomial Curve and Moving Average Combination Projection
TAS: thermal analysis computer system
US: United States
USA: United States of America